A Neural Network Inversion System for Atmospheric Remote-Sensing Measurements

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Abstract

A neural network inversion system is developed to retrieve physical properties of the atmosphere. The neural network has been trained with radiative transfer simulations, atmospheric measurements, and theoretical understandings about the physical properties and their signatures in satellite measurements. The learning and adjusting process will be very fast and automated. This study seeks to improve future remote-sensing algorithms by bridging visual understanding within the human brain and the retrieval techniques developed by researchers in scientific community. With the new inversion technique of remote-sensing measurements, we will greatly reduce the time and mass storage of conventional inversion methods.

Introduction

This study identifies the activities and resources planned to develop and verify a neural network inversion system to retrieve physical atmospheric properties. A simple case has been planned first; followed by systematically increasing the number of input parameters after careful analysis and verification. These activities include:

- Development of a database consisting of atmospheric radiative transfer simulated data and physical properties for training the neural network inversion system
- Development and training of the neural network models
- Applying the neural network to actual satellite measurements
- Verifying the neural network results to current retrieval results

Motivation

Since the 1970's, satellites have been making a global sampling of our Earth's system which are inherently unobtainable by ground-based systems. These remote-sensing measurements from space are rapidly increasing as satellites are launched with more sophisticated, hyper-spectral sensors. This trend will continue and the resulting high-volume of information collected from these satellite experiments include angular, spectral (UV, visible, IR and microwave) and spatial (both vertical and horizontal) dimensions. Physical properties of atmosphere, ocean, and land are mixed together in these observations. For most retrieval algorithms, adding new information to improve the retrievals of physical properties is not a simple task because of the nonlinear nature of the problem as well as the computational difficulties. This study intends to develop a neural network retrieval system that is capable of easily absorbing additional information.

Current Inversion Methods

The current inversion techniques include regression, lookup table searching, and iteration methods. For example, suppose **X** is a vector from satellite observations and **Z** is the physical properties to be retrieved. The functional relation, $\mathbf{X} = f(\mathbf{Z})$, is obtained by solving the radiative transfer equation. Mathematically, the inversion is to derive **Z** from **X**, or solving the inverse relation, $\mathbf{Z} = f^{-1}(\mathbf{X})$. If f is a linear function, a simple inversion method such as linear regression can be used to solve this equation. However, for most physical properties, the relationship between **Z** and **X** are highly nonlinear. The most popular inversion methods for these nonlinear problems are look-up table searching or iteration. As more and more sensors are added, the dimension of **X** increases and the inversion becomes a computational burden quickly. Both searching through an enormous lookup table and performing iterations over very many spectral channels are computationally expensive and the results may have difficulty converging. As a result, a small portion of the observations is effectively used in the retrievals.

Let's use cloud droplet size retrieval as an example here. Cloud particle size is a very important parameter for human-induced climate change studies. Activities such as industrial pollutions may cause changes in cloud particle sizes and thus alter the solar energy entering the Earth's climate system.

The physics of retrieving cloud particle sizes from satellite remote sensing is as following: cloud particles absorb near-infrared radiation (1-4 microns) from solar illumination, but they do not absorb in visible wavelengths. Larger particles absorb more near-IR radiation than smaller particles. As a result, for the same visible reflection, clouds with larger particles reflect less in near-IR comparing with clouds with smaller particles. At the mean time, we need to correct the thermal emission from clouds at near-IR wavelengths. To do that, we need to know the temperature of the clouds using a mid-IR channel emission at atmospheric window region (8-12 micron). Thus, deriving cloud particle sizes require radiance observations of at least 3 different wavelengths I ($I_{visible}$, $I_{near\text{-}IR}$ and $I_{mid\text{-}IR}$). Theoretical radiative transfer models compute these radiances for various combinations of cloud particle sizes (Re), optical thickness (τ) and temperatures (T). The theoretical radiative transfer models provide a mapping: (Re, τ, T) → ($I_{visible}$, $I_{near\text{-}IR}$, $I_{mid\text{-}IR}$).

Retrieving cloud particle size is an inversion process of the radiative transfer computations, which is a mapping: ($I_{visible}$, $I_{near\text{-}IR}$, $I_{mid\text{-}IR}$) → (Re, τ, T). Currently, such an inverse mapping (the retrievals) is performed either by searching through a huge look-up table of (Re, τ, T) → ($I_{visible}$, $I_{near\text{-}IR}$, $I_{mid\text{-}IR}$) derived from radiative transfer computations and finding the closest match, or by iterative processes of radiative transfer calculations for observations at each individual satellite pixel.

Neural Network Inversion Method

A neural network functional approximation is a significantly different way of handling the inversion, $\mathbf{Z}=f^{-1}(\mathbf{X})$. This approximation can be considered as a nonlinear multivariate regression problem with a special nonlinear orthogonal functional basis. If the inversion is well posed it can be accurately approximated by multi-layer neural networks as shown (left) in Figure 1 (Funahasi, 1989; Hornik, 1991; Haykin, 1999).

This network architecture (structure) is a feedforward back propagating network with one hidden layer. The function of the hidden layer is to intervene between the external input and the network output in some useful manner. By adding this hidden layer, the network is enabled to extract higher-order statistics which is particularly valuable when the size of the input layer is large and *the mapping is nonlinear*. The hidden layer, y_j, and the output layer, z_k, will use the activation function shown (lower panel) in Figure 1. This function is known as the sigmoid function and is by far the most common form of activation function used in the construction of artificial neural networks.

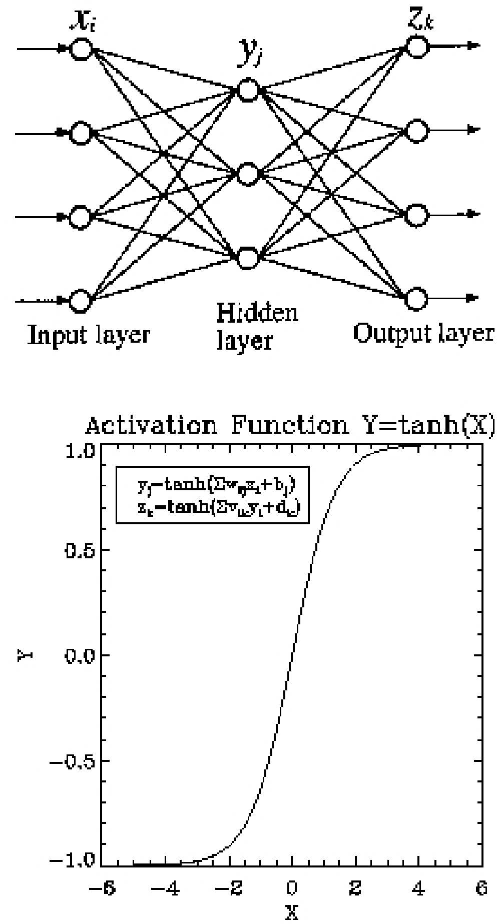

Figure 1. Fully connected feedforward or acyclic network with one hidden layer and one output layer (upper panel). The activation function is shown on the lower panel.

This neural network method is a major improvement over other retrieval methods because it has an obvious advantage in computational speed when applied to inversion techniques. Unlike the iteration technique, which needs to solve the very time-consuming radiative transfer equation hundreds of times for each sample of satellite measurements, neural networks only need a few simple operations and the inversion can be done in near real-time in comparison. To illustrate this fact, a very simple "test case" run was made using this neural network method, an iteration method, and a lookup table method. The time per inversion is shown in Figure 2 for one to six variables to be retrieved. (Note that the time scale is exponential.)

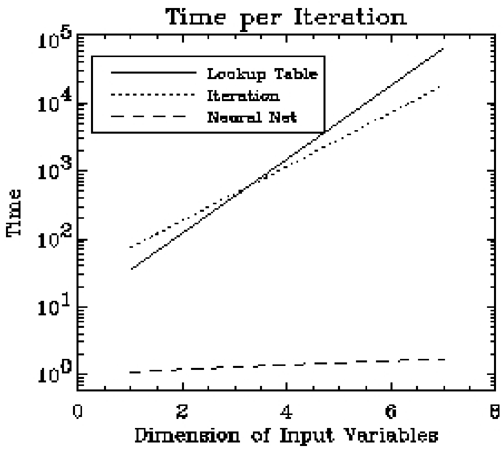

Figure 2. Comparison between Neural Network, Iteration, and Table Lookup Methods Time per Inversion

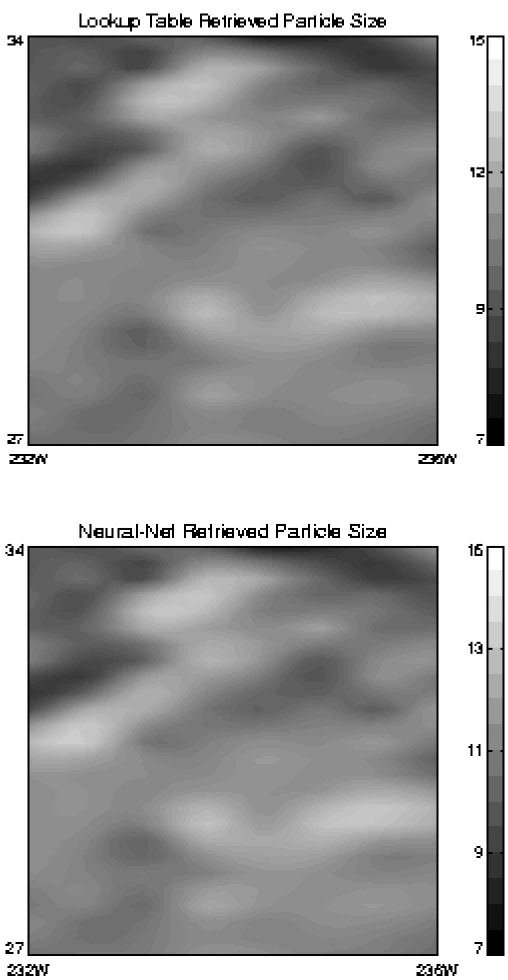

Figure 3. Cloud Particle Size Retrieval using Neural Network (upper) and Table Lookup (lower)

Generalized regression neural networks (GRNN) are another class of neural networks that are proven very effective functional approximation approaches. Comparing with back propagating (BP) method, GRNN is easier to train but more time consuming to apply with current computer capability. For our above retrievals, GRNN is close to look-up table in terms of computational speed.

In Figure 3, the retrieval for particle size is shown for the using the neural network (upper) and the lookup table method (lower) from AVHRR visible, near-IR and thermal IR channels. The lookup table approach is similar to the ones used by CERES cloud group at Langley and ISCCP project at GISS. The physical parameters (cloud particle size, water content and temperature) retrieved from the neural networks are almost identical to the ones from the lookup tables.

References

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